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Impacts of future climate and land cover changes on threatened mammals in the semi-arid Chinese Altai Mountains

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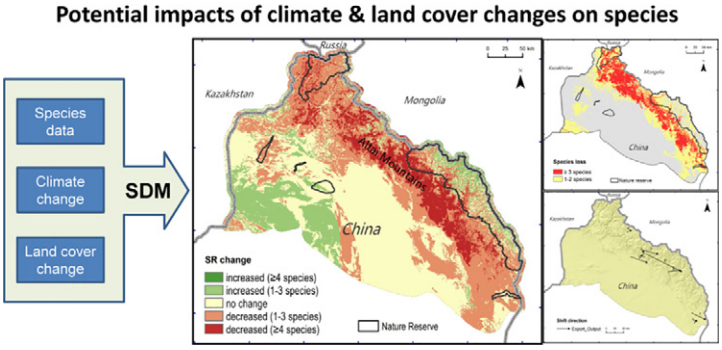
HIGHLIGHTS

- The semi-arid Altai Mountains are undergoing severe environmental changes.
- Species distribution modeling was used to predict range shifts of threatened mammals.
- Abrupt species range shifts are predicted under future climate & land cover changes.
- Remarkable declines in species assemblage and high rates of turnover are predicted.
- Expanding current reserve network and cross-border migration pathways are needed.

GRAPHICAL ABSTRACT



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ABSTRACT

Dryland biodiversity plays important roles in the fight against desertification and poverty, but is highly vulnerable to the impacts of environmental change. However, little research has been conducted on dual pressure from climate and land cover changes on biodiversity in arid and semi-arid environments. Concequntly, it is crutial to understand the potential impacts of future climate and land cover changes on dryland biodiversity. Here, using the Chinese Altai Mountains as a case study area, we predicted the future spatial distributions and local assemblages of nine threatened mammal species under projected climate and land cover change scenarios for the period 2010–2050. The results show that remarkable declines in mammal species richness as well as high rates of species turnover are seen to occur across large areas in the Chinese Altai Mountains, highlighting an urgent need for developing protection strategies for areas outside of current nature reserve network. The selected mammals are predicted to lose more than 50% of their current ranges on average, which is much higher than species' range gains (around 15%) under future climate and land cover changes. Most of the species are predicted to contract their ranges while moving eastwards and to higher altitudes, raising the need for establishing cross-border migration pathways for species. Furthermore, the inclusion of land cover changes had notable effects on projected range shifts of individual species under climate changes, demonstrating that land cover changes should be incorporated into the assessment of future climate impacts to facilitate biodiversity conservation in arid and semi-arid environments.

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1. Introduction

Climate change has been regarded as one of the major threats to biodiversity and ecosystems (Hansen et al., 2001; Travis, 2003). It can severely alter habitats and food sources for wildlife (Stenseth et al., 2002; Thomas et al., 2004) as well as the structure and function of ecosystems (Hughes, 2000; Parmesan and Yohe, 2003). Although many species are expected to shift their range boundaries in response to climate change (Davis and Shaw, 2001; Walther, 2010), there are fears that climate change is happening too fast for some species to adapt, thus ultimately leading to their extinction (Saxon et al., 2005). In addition to climate change, land cover change and its associated habitat fragmentation can also alter biological processes severely and decrease the quantity and quality of habitats (Fahrig, 2003; Root et al., 2003), thereby reducing opportunities for species to adapt, particularly the ability of species to relocate to more suitable habitats (Oliver et al., 2015; Pereira et al., 2012). Previous studies exploring species' responses to climate change have largely disregarded the role of landscape characteristics by assuming that species are limited only by the shift of climatic conditions (Currie, 2001; Roy et al., 2008). An implication of the lack of integrated analysis is that the potential effects of either climate change or land cover change per se are likely to be either over- or under-estimated (Chazal and Rounsevell, 2009). As regional land cover change may exacerbate or alleviate climatic impacts on biodiversity, it is important to integrate both factors to better understand potential impacts of future climate and land cover changes on biodiversity (Mcmahon et al., 2011).

Being central to the well-being and development of millions of people, dryland ecosystems play critical roles in the fight against desertification, climate change, and global poverty (Huang et al., 2016; Safriel and Tal, 2009). On the other hand, biodiversity in arid and semi-arid regions are highly vulnerable to environmental change, because many species already exist at the climatic and water thresholds for survival (Davies et al., 2012; Lioubimtseva et al., 2005). Projected future global warming may further exacerbate water scarcity, making the preservation of these fragile ecosystems even more challenging (IPCC, 2014b; Thomas et al., 2004). Improved knowledge of how dryland biodiversity reacts to climate change and its different levels of response to ongoing environmental change is of critical importance for preserving dryland ecosystems (Willis and Bhagwat, 2009). Developing proactive conservation plan for biodiversity requires accurate predictions of biological responses to potential environmental changes, the extent of expected change as well as the nature of habitat transformations under future climatic and land cover changes (Dawson and Mace, 2011). However, little research has been conducted on the impacts of climate and land cover change in arid environments. The lack of knowledge on how biodiversity would respond to these combined environmental changes greatly hamper the planning and implementation of sustainable biodiversity conservation in the context of climate change (Davies et al., 2012; Lioubimtseva et al., 2005).

The Altai Mountains are an extensive mountain range in arid central Asia, at the intersection of China, Russia, Mongolia and Kazakhstan. As part of the Altai-Sayan Ecoregion (one of the WWF's Global 200 Ecoregions), the Altai Mountains and their associated wetland ecosystems are well known for its unique biological and cultural diversity, and have provided critical ecosystem services such as regional water supply and climate regulation in arid central Asia (Kokorin et al., 2001; Olson et al., 2001). However, this mountainous region, especially the part within China, has received little attention to date (Lioubimtseva and Cole, 2006). Currently, only a Russian national strategy and a Mongolian government action plan for the conservation of Ibis (*Capra sibirica*) and Argali (*Ovis ammon*) have been developed, whereas no such efforts have been made within the Chinese part (WWF, 2010). As the dry southern part of the mountains, the Chinese Altai Mountains is situated in the northern part of Xinjiang Uygur Autonomous Region of China, in which semi-arid biodiversity is greatly threatened by natural and human-induced pressures including land degradation, livestock overgrazing, agriculture development, and climate change (Liu et al., 2002; Zhang et al., 2015). It has been reported that the annual average and maximum temperatures over this region for the period of 2000–2008 raised 3.34 °C and 7.02 °C respectively as compared to the period of 1957–1966 (Aizen et al., 2010). Such increase in temperature results in increased evaporation, which in turn changes vegetation through desiccation and with shifts in species composition (An et al., 2003; Li et al., 2006). It is thus crucial to understand how biodiversity would respond to future climate and land cover changes and develop effective conservation strategies in the context of climate change mitigation in the semi-arid Altai Mountains.

Using target groups of focal species to determine the status of biodiversity is a potential tool to design and assess conservation strategies. These species should be sensitive to environmental change and sampled efficiently in order to yield objective results (Moreno, 2007). Threatened and endangered mammal species are considered good indicators of climate change and land cover change effects on biodiversity, being characterized by narrow range shifts thereby limiting their adjusting to climate change (Hetem et al., 2014). Furthermore, if range shifts are likely to be the dominant species' response to future climate change, then spatially explicit planning will be fundamental to estimating the rate and direction of species displacements required to ensure retention of sufficient range for their future persistence (Midgley et al., 2003), and the analyses must be relevant at regional or sub-regional scales at which most practical conservation decisions are made.

In this study, we aim to assess regional impacts of climate and land cover changes on the future distribution of threatened mammal species in the semi-arid Chinese Altai Mountains. Using species distribution models, we simulated future distributions of these species based on the scenario data of climate and land cover changes, and analyzed its biological impacts by comparing species' current and future distributions under different assumptions of environmental change. This will allow the identification of future suitable habitats for threatened species and help inform priorities for regional conservation planning and biodiversity management in the semi-arid Altai Mountains.

2. Materials and methods

2.1. Study area and selected species

The study area is the southern part of the Altai Mountains (44°59′–49°20′N, 84°30′–90°57′E) that located in northern part of Xinjiang Uygur Autonomous Region of China (Fig. 1), with a total land area of 80,355 km^2. With a typically continental climate, annual average temperatures in this semi-arid region are between −4 °C and 3 °C, with the lowest and highest recorded temperatures being −51.5 °C and 41 °C, respectively; while annual precipitation, which mainly falls as snow, ranges from <100 mm on the plains to >600 mm on the high pastures (Li et al., 2012). The highest areas, following the ridgeline of the Chinese Altai Mountains, are comprised of alpine grasslands and wetland, while the vegetation in the mid-level altitudes includes more hemi-boreal forests with Siberian larch (*Larix sibirica*), Siberian pine (*Pinus sibirica*), and Siberian fir (*Abies sibirica*) (Chen and Yuan, 1989); to the south and west of the mountains, the habitat transitions into lower foothills with shrub cover and grassland; moving down and away from the mountains, the dominant habitat becomes arid and semi-arid steppe, dissected by the Ertix and Ulungur Rivers and their tributaries. The study area harbors 1378 species of flowering plants, 222 birds, and 54 mammals (Olson et al., 2001), including many valuable species for global biodiversity conservation. Currently there are six national and provincial level natural reserves, which cover around 13.6% of the land area.

In consideration of species popularity and data availability, the following locally rare and endangered mammal species were selected for study: Eurasian beaver (*Castor fiber*), Snow leopard (*Panthera unicia*), *Capra ibex* (*Capra sibirica*), Sable (*Martes zibellina*), Manul (*Otocolobus manul*), Moose (*Alces alces*), Argali (*Ovis ammon*), Red deer (*Cervus elaphus*), and Brown bear (*Ursus arctos*). These mammals are known

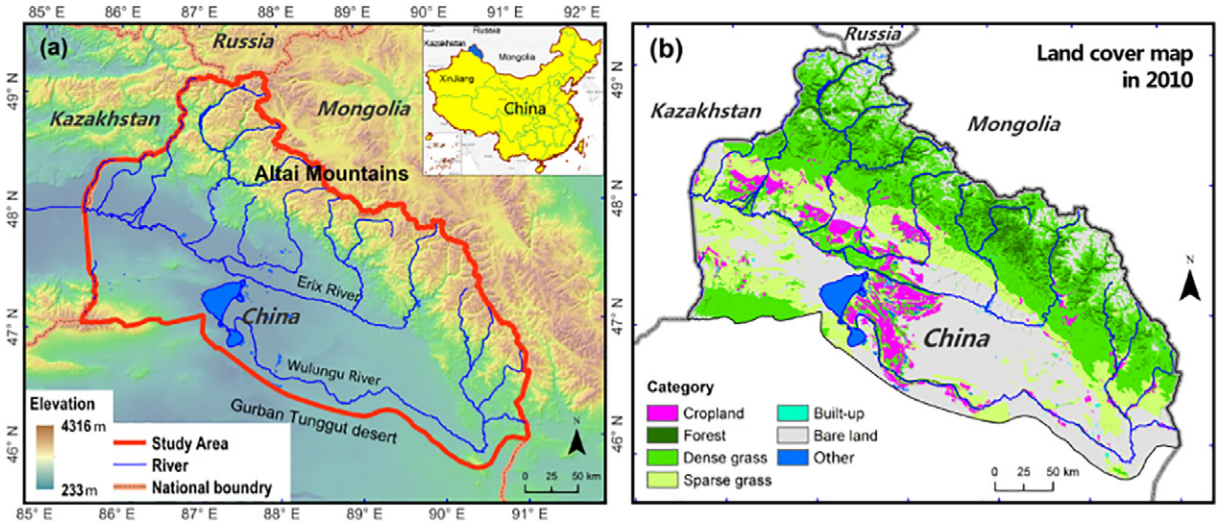

Fig. 1. Maps of the study area, showing (a) geographical location of the Chinese Altai Mountains with a digital elevation map in background, and (b) land cover patterns in 2010.

as the focal species in the Altai Mountains, and most of them are enlisted as endangered in National/Regional red list of threatened species (Table 1).

2.2. Species occurrence data

We combined the occurrence records of selected mammals from multiple sources including online spatial databases of IUCN Red List of Threatened Species (http://www.iucnredlist.org), Global Biodiversity Information Facility (GBIF; http://www.gbif.org), and field observations as well as published papers after 1990. The online spatial databases of IUCN Red List of Threatened Species and GBIF provide the current known distribution of the species within its native range based on known occurrences of the species along with the knowledge of habitat preferences, remaining suitable habitat, and current distribution extent (IUCN, 2013). To reduce potential errors in the data, records were "cleaned" through careful review of literatures for each species (Jones et al., 1989; Olson et al., 2001; Smith and Xie, 2010) with the removal of duplicate locations. Numbers of occurrence records per species are listed in Table 1.

2.3. Climate data and scenarios

We initially downloaded 19 bioclimatic variables (Table A.1) for both current climatic conditions (average for 1950–2000) and future projections (average for 2041–2060, hereafter referred to as 2050) from the WorldClim Dataset (www.worldclim.org), with a 30 arc-seconds (~1 km) resolution (Hijmans et al., 2005). These variables describe annual and seasonal trends of temperature and precipitation and allow for an adequate characterization of the species bioclimatic niches.

With an aim of capturing plausible variations in future climate (Taylor et al., 2012), projections of climate for 2050 were extracted from nine global climate models (GCM) used in the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC): BCC-CSM1-1, CCSM4, MIROC5, MIROC-ESM, GISS-E2-R, HadGEM2-AO, HadGEM2-ES, IPSL-CM5A-LR, and MRI-CGCM3 (see IPCC, 2014b for model details). There are four representative concentration pathways (RCP) scenarios available for climate projections from GCMs, representing a possible range of changes in future anthropogenic greenhouse gas (GHG) emissions (Reisinger et al., 2011). In this analysis, we chose future climate projections under RCP4.5 (IPCC, 2014a), an optimistic scenario assuming that global annual GHG emissions peak around 2040 (Meinshausen et al., 2011) as well as a mean global temperature increase of 1.4 °C by mid-21st century (Alexander et al., 2013).

Prior to the species-climate modeling, we tested for multicollinearity among the 19 current bioclimatic variables and found that eight out of the 19 variables were most correlated with others (Table A.2) and were excluded from the following analysis: viz. annual mean temperature (BIO1), temperature seasonality (BIO4), max temperature of warmest month (BIO5), mean temperature of wettest quarter (BIO8), mean temperature of warmest quarter (BIO10), precipitation of wettest month (BIO13), precipitation of wettest quarter (BIO16), and precipitation of warmest quarter (BIO18).

Table 1
Nine selected threatened mammal species, their conservation status on the IUCN Red List as well as China State Protected List, and number of occurrences used in species distribution modeling.

Common name	Scientific name	IUCN 2010 category[a]	National red list category[b]	Number of occurrences
Eurasian beaver	*Castor fiber*	LC	EN	34
Snow leopard	*Panthera unicia*	EN	EN	36
Asiatic ibex	*Capra sibirica*	LC	NT	132
Sable	*Martes zibellina*	LC	VU	71
Manul	*Otocolobus manul*	NT	EN	43
Moose	*Alces alces*	LC	EN	112
Argali	*Ovis ammon*	NT	EN	210
Red deer	*Cervus elaphus*	LC	CR	285
Brown bear	*Ursus arctos*	LC	VU	150

[a] Status of the species according to the IUCN 2010 red list of threatened species: LC, least concern; NT, near threatened; VU, vulnerable; EN, endangered; CR, critically endangered. See http://www.iucnredlist.org/static/categories_criteria_3_1.
[b] Status of the species according to the National/Regional red list of threatened species: LC, least concern; NT, near threatened; VU, vulnerable; EN, endangered; CR, critically endangered. See http://www.nationalredlist.org for further information.

2.4. Land cover data and the simulation of future changes

We simulated the future situation of land cover in 2050 based on historical changes in land cover patterns in 2000 and 2010 (see Fig. A.1). The flowchart of the land cover change simulation is shown in Fig. 2a. The land cover maps for 2000 and 2010 were derived from Moderate Resolution Imaging Spectrometer (MODIS) imagery at a resolution of 1 km (Channan et al., 2014), and contain 17 land cover classes in the International Geosphere-Biosphere Programme (IGBP) classification scheme (Friedl et al., 2010). To facilitate the projection of land cover change, the 17 IGBP classes were aggregated into seven land cover classes: viz. cropland, woodland, dense grassland, sparse grassland, urban and built-up, bare land, and other (water bodies and snow/ice). The future land cover patterns for 2050 were projected using the Markov-CA (Cellular Automata) model in the Idrisi software (Eastman, 2015), which is a robust tool for land cover change projection using Markov chain and Cellular Automata (Sang et al., 2011). We first developed land cover transition potentials for the period 2000–2010 through the Markov chain analysis on changes between land cover maps of 2000 and 2010. The probability of change (transition probability) between two time periods was then quantified using the Markov transition matrix. We assumed the transition probabilities remain unchanged over time, and used it to project future land cover patterns for 2050 through the CA model. We incorporated several natural and socioeconomic data layers (i.e., elevation, slope, distance to roads, distance to urban, and population density) into the generation of transition potential maps to further improve the simulation accuracy of Markov-CA model (Riccioli et al., 2013). Afterward, land cover change was estimated using the "Area" module in Idrisi, and each land cover map for 2010 and 2050 was entered as a categorical variable for the species distribution modeling for the respective time periods.

2.5. Modeling species distributions

We built individual models for each species using the maximum entropy (MaxEnt) approach (Phillips et al., 2006). MaxEnt models the climate-constrained probability of a species' distribution based on presence-only data (Elith et al., 2006), with an advantage over other species distribution models (SDMs) that both continuous and categorical variables can be input to model (Baldwin, 2009). The conceptual flowchart of species distribution modeling is shown in Fig. 2b. Following the methodology of Elith et al. (2010), we randomly divided each species' occurrence points into two subsets: 70% for model calibration and 30% for model validation. The maximum number of background points for sampling was kept at 10,000, and the maximum iteration for each run was set to 1000 to ensure the model has adequate time to converge. We executed 10 replicates using repeated split samples to measure the amount of variability in the model and then averaged the results. The importance of each predictor variable was described using the permutation importance (Altmann et al., 2010).

Model performance was initially evaluated by calculating the area under the receiver operating characteristic curve (AUC; Lobo et al., 2008), where values of AUC range from 0.5 for models with no predictive ability to 1.0 for models giving perfect predictions. As the AUC has been criticized as assessing the degree to which predictors can restrict species range rather than model performance (Lobo et al., 2008), we further employed the true skill statistic (TSS) as a further test of model performance. The TSS avoids reliance on prevalence or size of validation set, and is thus a good measure of predictive accuracy of presence-only models (Allouche et al., 2006). TSS values also range from 0 to 1, with values >0.6 being considered good performance.

We projected the fitted models onto both the current environmental conditions and future environmental scenarios for 2050. The probability of species' presence generated from the species distribution model was then transformed into presence–absence using a threshold maximizing the sum of sensitivity and specificity (Max SSS). The Max SSS threshold can minimize the mean of the error rate and has been widely used in SDMs (Liu et al., 2013). Since only one projection per species was required for impact assessment, we stacked all binary distribution projections from the nine GCMs to explore central tendencies in projections, and selected overlap areas among projections as future distribution range (Thuiller, 2004).

To investigate how future land cover change would affect species distributions, we repeated the SDMs using the different future climate conditions but fixing the land cover variable to the observed 2010 land cover map, i.e., assuming the land cover patterns will not change in the future. The relative effect of future land cover change was then examined by comparing the results from two different scenarios. The

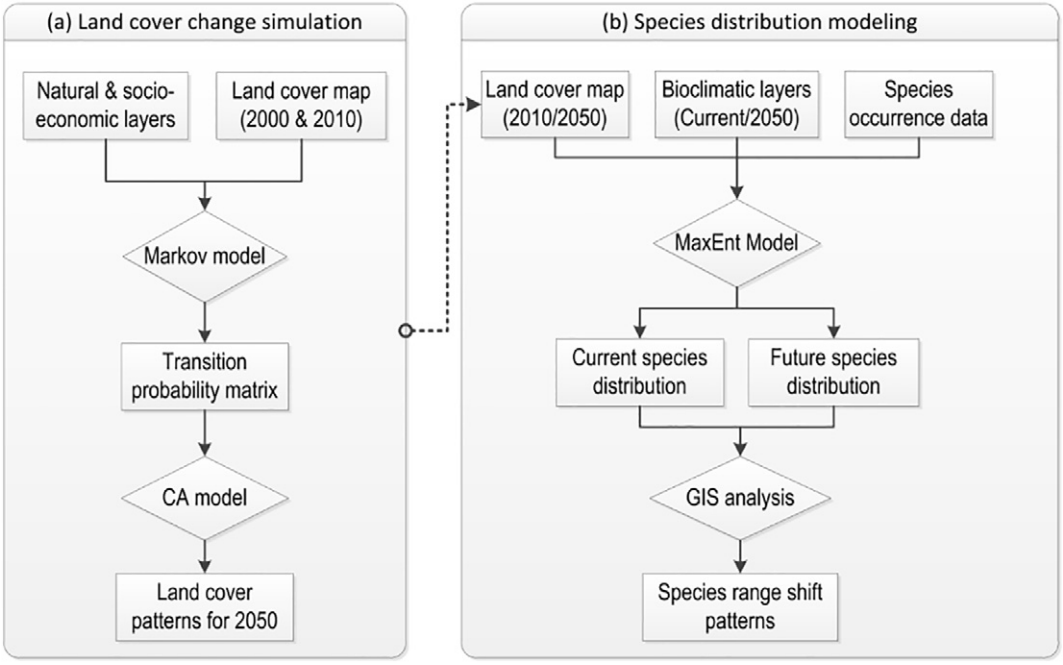

Fig. 2. The workflows of (a) land cover change simulation, and (b) species distribution modeling in the research.

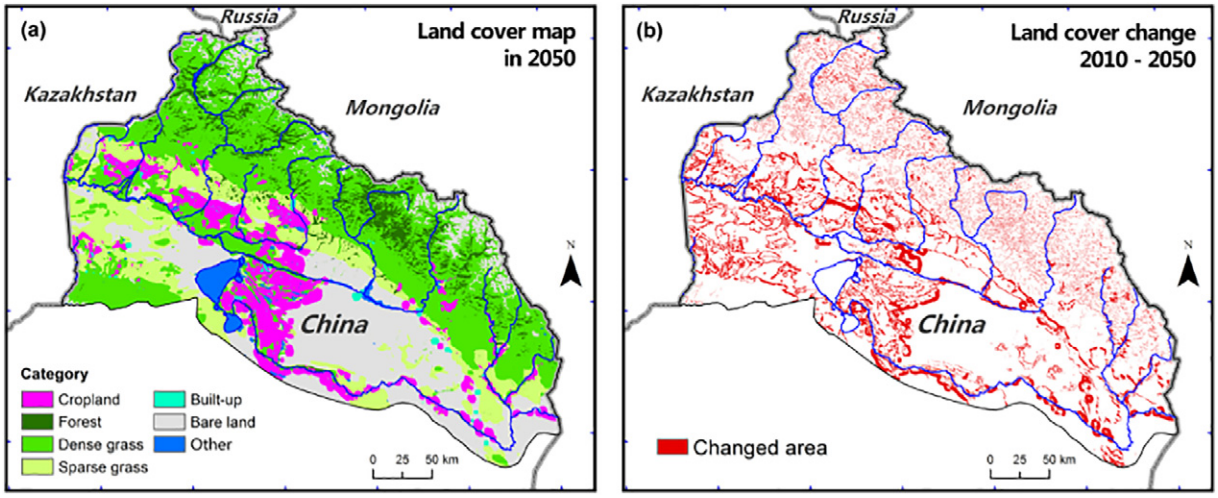

Fig. 3. The simulated land cover changes, showing (a) the future land cover pattern for 2050, and (b) land cover change between 2010 and 2050.

study of land cover changes under different socioeconomic trends appears to be warranted, but is beyond the scope of the paper.

2.6. Assessing species responses to environmental change

To assess the level of environmental impacts on the selected species, we estimated range persistence, range gain, and range loss for each species by intersecting each species' current and future distribution maps. Species' range persistence was calculated as the percentage of overlapping area between current and future distributions relative to its current area (Richardg et al., 2006), while species' range gain and loss were computed as the percentage of area predicted to become suitable or unsuitable respectively in the future relative to its current area (Broennimann et al., 2006). Species' range change was then calculated as the difference between range gain and loss, representing the percentage of range expansion or contraction between current and future scenarios (Ramirez-Villegas et al., 2014). The distance and direction of species' range shifts were estimated based on range centroids of current and future distributions.

The impacts of environmental change on each species spatial assemblages were examined by calculating the differences between future species richness (SR) and current SR, in which the SR was calculated as the total number of species present in each pixel (Broennimann et al., 2006). The species turnover rate was estimated based on 'species gain' (i.e. number of species predicted to newly arrive in the future) and 'species loss' (i.e. number of species no longer be present in the future) in each pixel (Broennimann et al., 2006): species turnover = 100 × (species gain + species loss)/(initial species richness + species gain). A turnover value of zero indicates that the assemblage of species is predicted to be unchanged (i.e. no loss or gain of species), whereas a value of 100 indicates that there is a complete species changes. Note that this turnover index describes the relative magnitude of the change in local species richness rather than in community structure. The depiction of exact change in local species composition is possible but unnecessary in this study, since we investigated only a small number rather than large taxa of species.

3. Results

3.1. Predicted land cover change between 2010 and 2050

The future land cover map generated by the Markov-CA model is presented in Fig. 3a. The simulation results indicate that, if the transition continues at the same rate as for the past decade (i.e., 2000–2010), the study area would experience dramatic land cover changes by 2050, mostly in the Ertix River Basin and along the Wulungu River (Fig. 3b). Compared to 2010, the area of cropland, built-up land, and dense grassland would increase by 87.78%, 106%, and 11.74% by 2050, respectively; while areas of sparse grassland, woodland, and bare land would decrease by 5.95%, 14.48%, and 21.24%, respectively (Table 2 and Table A.3).

3.2. Predictive performance of MaxEnt models

The MaxEnt models generally show good predictive performance (test AUC: 0.859–0.989; TSS: 0.59–0.67). The permutation importance of each variable varied considerably between species (Fig. 4 and Table A.4). In general, precipitation seasonality (BIO15) had the greatest permutation importance, followed by annual precipitation (BIO12) and minimum temperature of coldest month (BIO6), indicating that precipitation was more important in the predictive models than temperature (Fig. 4). Land cover was generally less important for most species (permutation importance 0.17–6.98%), suggesting that the distributions of selected mammals might be governed, to a large extent, by climatic factors at the regional scale.

3.3. Changes in species assemblage and turnover

The change map of species richness suggests that selected mammals would experience strong upslope shifts under future climate and land cover changes (Fig. 5a). Areas with the largest decreases in species richness were located along the outer slopes of the Chinese Altai Mountains between 1500 and 2000 m (Fig. 5a). Under current environmental conditions, the highest concentration (i.e., ≥3 species) of the nine selected species was primarily located along the montane forests between 1500 and 3000 m throughout the Chinese Altai Mountains, whereas the highest density area by 2050 was predicted to shift to the southeastern part of the mountains between 2000 and 3000 m (Fig. A.1). It is noted

Table 2
Summary statistics of land cover patterns and their changes for the period 2010–2050. Area change per category was calculated as the difference in area between 2010 and 2050 relative to the area in 2010.

Land cover category	Area (km^2)			Change in 2010–2050 (%)
	Year 2000	Year 2010	Year 2050	
Cropland	2608	4741	8903	87.78
Woodland	8201	6059	5698	−5.95
Dense grassland	23,415	27,023	30,195	11.74
Sparse grassland	15,772	15,003	12,830	−14.48
Urban and built-up	96	265	545	106.12
Bare land	28,480	25,487	20,075	−21.24
Other	1783	1778	2107	18.54

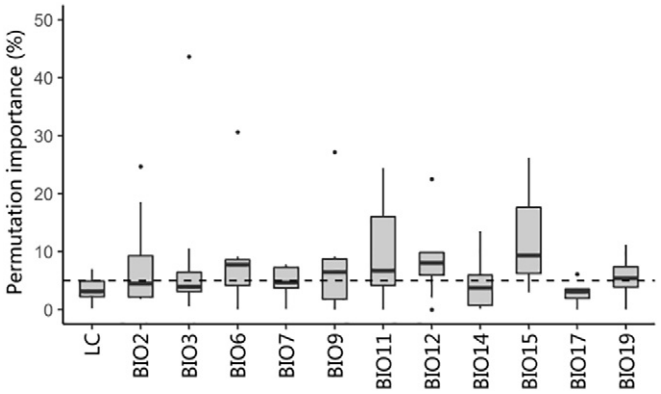

Fig. 4. Permutation importance of each predictor variable in SDMs. Boxplot shows 10th, 25th, 50th, 75th and 90th percentiles. The dashed line indicates the median of permutation importance over all predictor variables.

that a significant reduction in species richness was observed within the area of Kanas Nature Reserve, in contrast to Liangheyuan Nature Reserve where the species richness displayed a positive changes by 2050 (Fig. 5a). The pattern of changes in species richness simulated without future land cover change (Fig. 5b) was generally consistent with the pattern generated under both climate and land cover changes (Fig. 5a).

The projected species turnover by 2050 displayed similar patterns to the changes of species richness (Fig. 6), which were concentrated to a large extent in the lower altitude mountainous area and plains of Wulungu Lake and Erix river basin (Fig. 6). The highest species loss was expected to occur in the area of the Chinese Altai Mountains between 1500 and 2000 m (Fig. 6a). The inclusion of land cover change resulted in marked changes in spatial patterns of species turnover in medium and low altitude areas (Fig. 6, Fig. A.2, and Fig. A.3).

3.4. Responses of individual species

As expected, the impact of environmental change on each species involved range contraction for the period 2010–2050 (Table 3 and Fig. 7). When modeled with combined land cover and climate change, the area change of individual species varied from −98.99% to −1.84% (Table 3), and six species would reduce their distribution range by >50% by 2050 (Fig. 7a and Fig. A.4). In contrast, the area change for species varied from −98.02% to10.23% under the scenario with climate change only (Table 3), and seven species would show substantial range loss (>50%) in their original range (Fig. 7b and Fig. A.4). It is interesting that the Asiatic Ibex could have a range expansion of 10.23% when modeled without land cover change, contrasting with a slight range shrinking under the assumption with combined land cover and climate change (Table 3). Conversely, Snow Leopard and Manul would undergo more severe range contractions when modeled without land cover change, highlighting specific sensitivities to future land cover changes (Table 3).

Shifts of range centroids were usually oriented eastward but varied across species (Fig. 8). The average expected range shift (distance between current and future range centroids) for all species was 40 km (range 9–115 km) under the scenario with combined land cover and climate change (Table 3). Surprisingly, the red deer displayed the largest potential range shift (~115 km) among nine selected species (Fig. 8a and Table 3). The range shift of the snow leopard was the lowest, with a distance of ~9 km. The inclusion of land cover change had unapparent influence on simulated range shifts of all species except for the brown bear which would shift southwest when modeled with combined land cover and climate change, in contrast with an eastward shifting under the scenario of climate change only (Fig. 8).

4. Discussion

We investigated the potential effects of climate and land cover changes on nine threatened mammals in the semi-arid Chinese Altai Mountains region. Our assessment is timely in that the species diversity in this semi-arid region is facing increasing habitat degradation and human disturbance, but still poorly understood to date (Kokorin et al., 2001). The results suggest that the impacts of climate and land cover changes over the semi-arid Altai biota could be extremely severe, which is generally consistent with the findings of other research that there can be profound effects on the distribution of animal species as climatic shifts to warmer and drier regimes (Hetem et al., 2014; Wu, 2015). In the context of biodiversity conservation, the effectiveness of the current protected area system under the challenges of climate and land cover change is a critical question that we must answer (Beaumont et al., 2011; Chlachula and Sukhova, 2011). Although it is very likely that individual responses at the species level will be determined by species' ecological traits (i.e. dispersal capacity) as well as their tolerances to environmental stresses, our estimates are capable of gauging general trends and possible impacts suffered by species and community, providing useful knowledge for conservation planning (Rodrigues and Brooks, 2007).

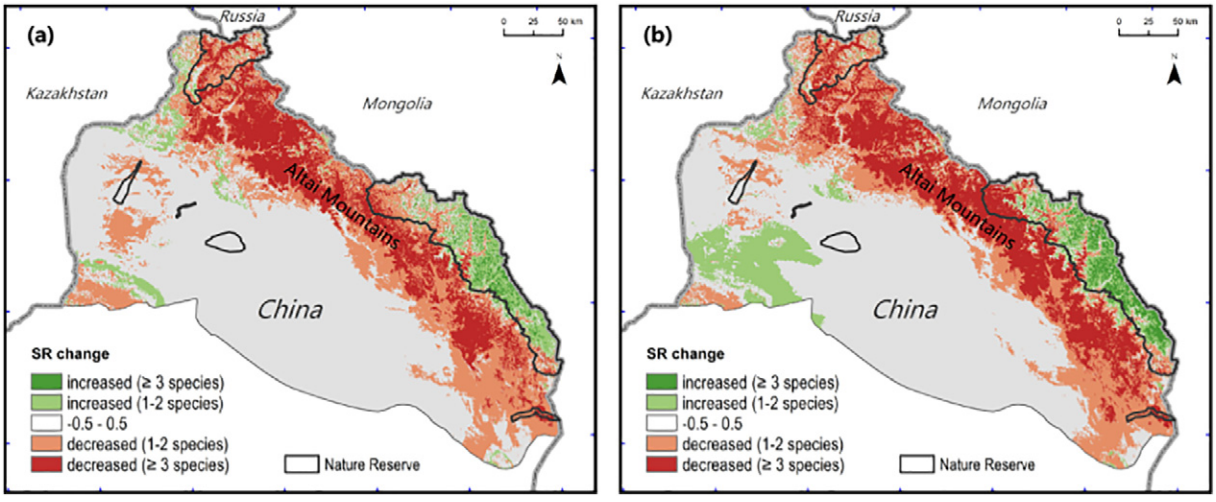

Fig. 5. Spatial patterns of changes in species richness of the selected species for the period 2010–2050, simulated by (a) SDMs with combined climate and land cover changes, and (b) SDMs with climate change only, respectively.

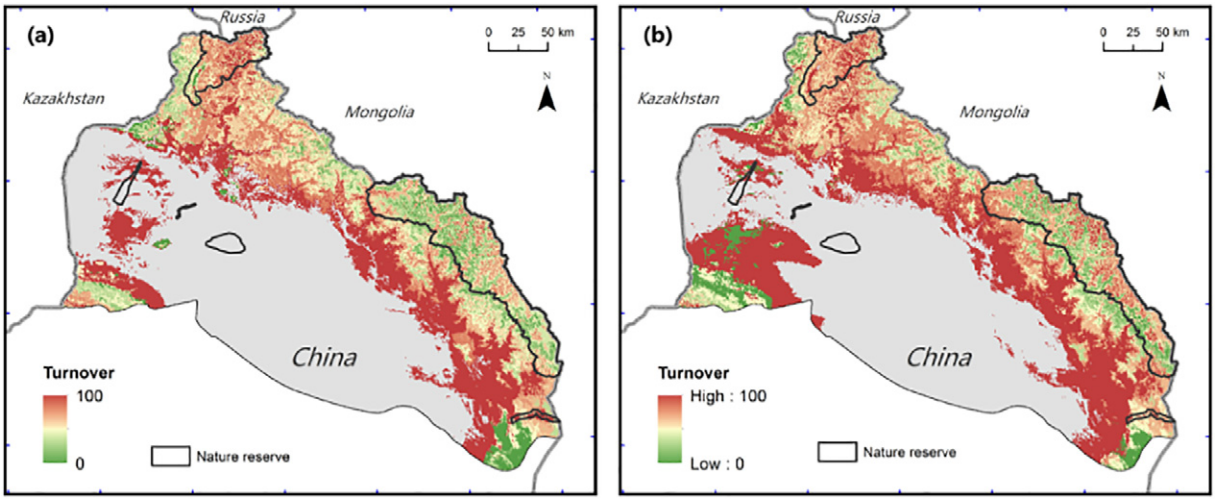

Fig. 6. Spatial patterns of species turnover of the selected species for the period 2010–2050, simulated by (a) SDMs with combined climate and land cover changes, and (b) SDMs with climate change only, respectively. Values are percentages of change in community turnover by 2050.

Our simulations indicate that the combined impacts of future climate and land cover changes on threatened mammals might be even more severe than expected outside the protected areas, where remarkable declines in mammal species richness as well as high rates of species turnover were predicted. At the regional level, the montane forests along outer slopes (between 1500 and 2000 m) of the Chinese Altai Mountains are likely to be the most affected due to a high amount of species loss. This likely poses great challenge for biodiversity conservation in the existing protected areas as well as the whole semi-arid Chinese Altai Mountains. The spatial and temporal asynchronies between mutualistic species would cause the changes in community composition and structure, which further alter the functional connectivity of landscapes as well as ecosystem services (Zavaleta et al., 2003). At the species level, two-thirds of the selected mammals were estimated to lose >50% of their original distribution space, indicating these species are likely to face a heightened risk of extinction by 2050 (Fig. 5 and Fig. A.4). These climate-sensitive species, such as Eurasian beaver and Sable, should therefore be prioritized for further assessment of potential impacts of climate and land cover changes on biodiversity as well as ecosystem services (Moreno, 2007).

Although climate and land cover changes are two of the primary threats to global biodiversity, they are usually considered independently (Brodie et al., 2012). In particular, there is no research on the joint effects of future climate and land cover changes on biodiversity for our study area. We therefore cautiously compared the results with other studies addressing the synergic impact of climate and land cover changes. A few studies included land cover change scenarios when predicting species' range shifts and suggested that climate change has a stronger effect on species distribution than land cover change (e.g., Martin and Titeux, 2013). However, Struebig et al. (2015) found a more marked retraction of species when including future land cover changes in projected distributions. The present study confirms the importance of accounting for land cover change when assessing species responses for conservation planning: for most of the selected mammals, the combination of climate change and future land cover change had greater effects on changing the distribution areas than those with present land cover patterns only (Schmitz et al., 2015). Although climate variables contributed more to our model results than land cover data (Fig. 3), the addition of land cover data to climate-based models refined modeled species ranges in most cases. From an ecological point of view, climate has the dominant impact on species' regional range shifts, yet land cover change would affect local accessibility of suitable habitats by species (Perring et al., 2015). Modeling species' climate-constrained range changes in the absence of corresponding land cover change may result in the misrepresentation of future range either positively or negatively, dependent upon whether projected land cover change is harmful or beneficial to a species (Martin and Titeux, 2013). Therefore, further studies should focus on the roles of finer scale anthropogenic changes to improve our understanding of species' responses in the context of climate change (Keith et al., 2008; Margules and Pressey, 2000). In addition, systematic monitoring of key species in different land cover types could greatly help in identifying where corridors should be established, enhanced or preserved in human-modified landscapes (Bond, 2003).

Effective climate change mitigation requires an integrated set of ecological, political, economic, and sociological approaches, yet can be

Table 3
Projected range changes of individual species by 2050 under different environmental change scenarios. Area change per species was calculated as the differences between current and future range sizes relative to its current range size. Distance and direction of species' range shifts were estimated based on centroids of the modeled current and future distributions.

Species	SDMs with combined land cover and climate change			SDMs with climate change only		
	Area change (%)	Distance of range shift (km)	Direction of range shift	Area change (%)	Distance of range shift (km)	Direction of range shift
Eurasian beaver	−98.99	45	E	−98.02	42	E
Snow leopard	−23.19	9	NE	−44.95	18	E
Asiatic ibex	−1.84	15	W	10.23	20	NW
Sable	−91.67	16	E	−91.22	24	E
Manul	−3.94	12	N	−24.15	23	NE
Moose	−43.95	37	E	−40.14	37	E
Argali	−71.55	47	E	−69.67	58	E
Red deer	−33.41	115	E	−19.31	107	E
Brown bear	−82.61	52	E	−87.55	33	SW

Note: E = East; W = West; N = North; NE = Northeast; NW = Northwest; SW = Southwest.

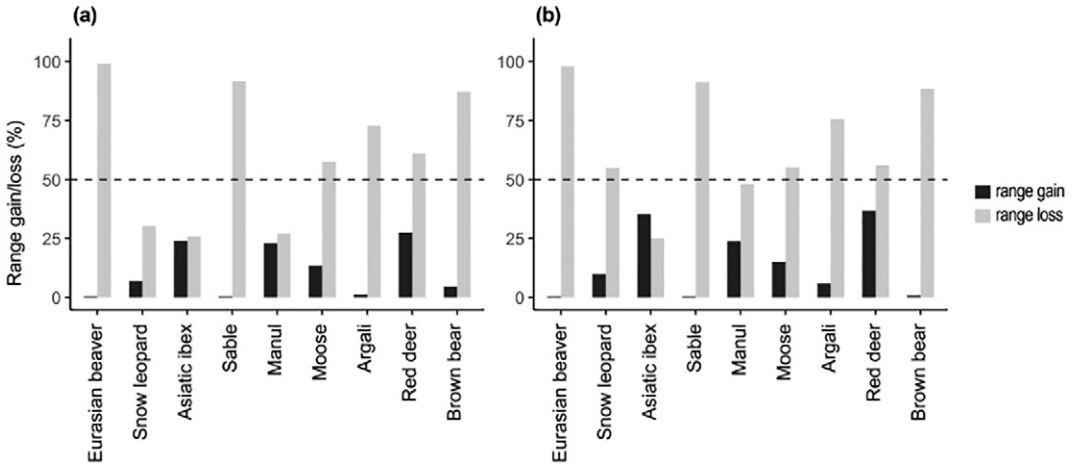

Fig. 7. Predicted range gain/loss of selected species by 2050, simulated by (a) SDMs with combined climate and land cover changes, and (b) SDMs with climate change only, respectively.

constrained by many local/regional characteristics (Hannah et al., 2002). In the present study, we focused only on the Chinese part of the Altai Mountains, which comprise about 10% of the whole mountain range. Thus the findings should be interpreted with caution when they are applied to other parts of the Altai Mountains. We acknowledge that an assessment of species' responses to future climate change at a geographic level is necessary. However, our study area is more like an isolated 'island' owing to massive barbed wire fences along China's border. The lack of relevant information (e.g., detailed land cover data) also precludes the projection of species' future beyond the present study area. With respect to the Chinese part of the Altai Mountains, species assemblages were predicted to decrease significantly outside the reserves, which would pose great challenges for safeguarding climate-sensitive species and biodiversity. The abrupt changes in areas surrounding existing protected zones would decrease the connectivity of the landscape and further become the 'ecological traps' for wild animals in the landscape. Therefore, an urgent need for biodiversity conservation is to develop effective protection strategies for areas outside of current reserves. To this end, special focus should be addressed to identify priority areas for design (or adjustment) of protected area system for biodiversity conservation. Moreover, the upslope and eastward shifts of species also raise the need for a wide range of adaptation pathways such as migration corridors and 'stepping stones' for species (Hetem et al., 2014). However, there are massive barbed wire fences along China's border (mostly on the ridge) with Mongolia and Russia, which can severely interrupt cross-border migration of large mammals and greatly reduce the space for species' range displacement in response to future climate change. Therefore, it is necessary to raise awareness and transboundary cooperation for establishing movement links and migration 'stepping stones' across country borders (Schmitz et al., 2015; Williams et al., 2010).

There are several sources of uncertainty in the present study, which may influence the results we draw here. Our models assumed all species are affected only by climate and land cover patterns and can move freely to climatically suitable areas, by which the real effects of environmental change and land cover changes are simplified. Furthermore, the measure of species turnover adopted in the analysis does not allow identification of the changes in structure of local community. A detailed assessment of relevant local processes and their effects on ecosystem function is necessary since changes in structure and dynamics of communities might greatly affect ecological services of the ecosystems (Ledger et al., 2012). Nevertheless, our results do provide important information about the potential effects of future climate change and

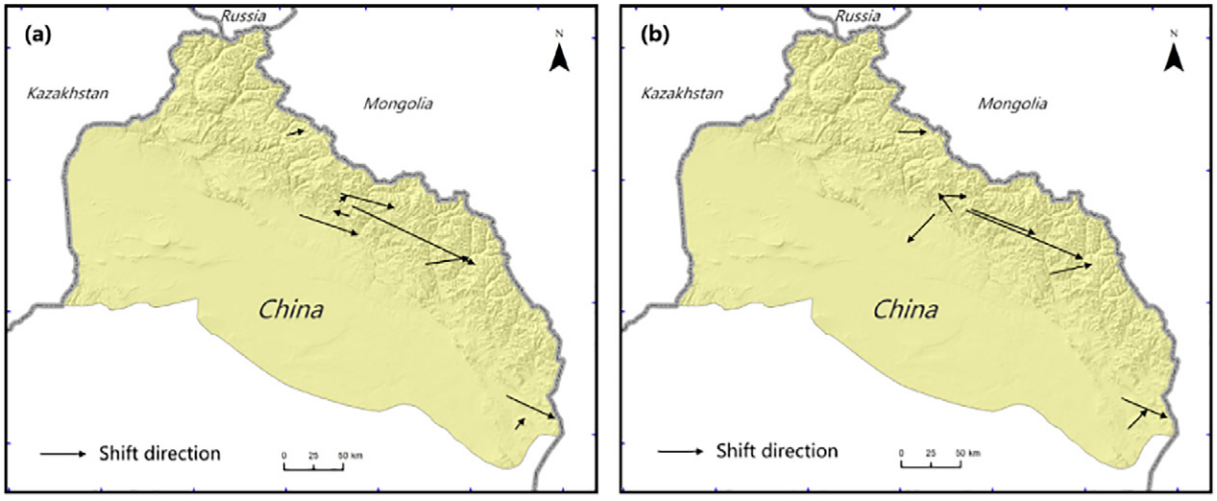

Fig. 8. Predicted range shifts of individual species from (a) SDMs with combined climate and land cover changes, and (b) SDMs with climate change only. Base and tip of arrows represent centroids of species' current and future distribution, respectively.

species' possible trends of migration (Duan et al., 2016; Thuiller et al., 2006). The herein projected changes in species distribution and richness are useful metrics in conservation planning, such as for evaluation of effectiveness of protected area system and delimitation of priority conservation areas and conservation targets under future climate change (Ramirez-Villegas et al., 2014).

5. Conclusions

In conclusion, this study represents the first assessment of the potential effects of future climate and land cover changes on species in the semi-arid Chinese Altai Mountains region. Our analyses demonstrated that the combined effects of future land cover and climate changes could have remarkable effects on the species' distributions and local richness in that all selected mammals displayed acute range shifts under future climate and land cover changes. The results identified additional priority conservation areas along the outer slopes of the Chinese Altai Mountains between 1500 and 2000 m, where remarkable declines of species richness would occur under future climate and land cover changes in the semi-arid Altai Mountains. We suggest routinely including climatic-sensitive species and montane forests into current monitoring network and ecosystem service assessments. While predicting a pessimistic outlook for Altai's biodiversity, our analyses demonstrate that an evaluation of the conservation estate could be beneficial to best planning for biodiversity conservation in face of land cover and climate change. In particular, incorporating land-use change into the assessment of future climate impacts will be necessary to meet biodiversity goals under dynamic threats in arid environments.

Acknowledgements

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Appendix A. Appendices

Table A.1
Descriptions of 19 bioclimatic variables used for species distribution modeling.

Variable abbr.	Description
BIO1	Annual mean temperature
BIO2	Mean diurnal range (mean of monthly (max temp - min temp))
BIO3	Isothermality (BIO2/BIO7) (*100)
BIO4	Temperature seasonality (standard deviation *100)
BIO5	Max temperature of warmest month
BIO6	Min temperature of coldest month
BIO7	Temperature ANNUAL Range (BIO5-BIO6)
BIO8	Mean temperature of wettest quarter
BIO9	Mean temperature of driest quarter
BIO10	Mean temperature of warmest quarter
BIO11	Mean temperature of coldest quarter
BIO12	Annual precipitation
BIO13	Precipitation of wettest month
BIO14	Precipitation of driest month
BIO15	Precipitation seasonality (coefficient of variation)
BIO16	Precipitation of wettest quarter
BIO17	Precipitation of driest quarter
BIO18	Precipitation of warmest quarter
BIO19	Precipitation of coldest quarter

Table A.2
Testing for multicollinearity among 19 bioclimatic variables.

Bioclimatic variable	BIO2	BIO3	BIO4	BIO5	BIO6	BIO7	BIO8	BIO9	BIO10	BIO11	BIO12	BIO13	BIO14	BIO15	BIO16	BIO17	BIO18	BIO19
BIO1	0.29	−0.69	0.87	0.99	0.75	0.75	0.98	0.94	1	0.92	−0.62	−0.86	0.37	−0.89	−0.85	0.26	−0.85	0.32
BIO2		0.39	0.65	0.39	−0.39	0.82	0.36	0.08	0.36	−0.07	−0.63	−0.55	−0.16	−0.27	−0.6	−0.19	−0.58	−0.28
BIO3			−0.43	−0.64	−0.87	−0.19	−0.63	−0.74	−0.66	−0.8	0.1	0.42	−0.51	0.68	0.36	−0.43	0.38	−0.55
BIO4				0.93	0.36	0.97	0.88	0.71	0.92	0.61	−0.71	−0.9	0.28	−0.85	−0.9	0.18	−0.9	0.19
BIO5					0.67	0.82	0.98	0.91	1	0.86	−0.65	−0.89	0.37	−0.9	−0.88	0.26	−0.88	0.3
BIO6						0.13	0.69	0.86	0.69	0.94	−0.16	−0.43	0.45	−0.63	−0.39	0.36	−0.41	0.47
BIO7							0.78	0.56	0.81	0.43	−0.75	−0.86	0.15	−0.72	−0.87	0.07	−0.87	0.05
BIO8								0.92	0.98	0.88	−0.67	−0.88	0.3	−0.85	−0.87	0.19	−0.87	0.25
BIO9									0.91	0.96	−0.48	−0.74	0.42	−0.84	−0.72	0.32	−0.72	0.4
BIO10										0.87	−0.65	−0.89	0.36	−0.9	−0.88	0.25	−0.88	0.3
BIO11											−0.42	−0.67	0.39	−0.76	−0.65	0.29	−0.65	0.38
BIO12												0.91	0.42	0.34	0.92	0.52	0.92	0.47
BIO13													0.02	0.69	0.99	0.14	1	0.09
BIO14														−0.67	0.05	0.98	0.03	0.97
BIO15															0.67	−0.59	0.68	−0.61
BIO16																0.16	1	0.11
BIO17																	0.15	0.97
BIO18																		0.1

Bold indicate significance at $p < 0.05$.

Table A.3
Projected land cover conversions between categories for the period of 2010–2050.

land cover category	Area of conversion (km^2)				
	Woodland	Dense grassland	Sparse grassland	Urban and built-up	Bare land
Cropland	152	861	1001	−11	2152
Woodland		−484	351	−11	−28
Dense grassland			2507	−47	1084
Sparse grassland				−56	1789
Urban and built-up					154

Table A.4
Permutation importance of each predictor in SDMs for nine selected mammal species.

Species	Predictor variable											
	land cover	BIO2	BIO3	BIO6	BIO7	BIO9	BIO11	BIO12	BIO14	BIO15	BIO17	BIO19
Eurasian beaver	0.17	**18.566**	**67.99**	0.38	7.54	0.00	0.00	0.00	0.17	2.94	0.15	0.01
Snow leopard	6.98	2.17	3.96	8.11	4.71	**27.16**	6.72	6.42	3.89	9.36	6.12	3.87
Asiatic ibex	4.91	5.58	10.55	7.14	3.08	6.90	4.39	9.90	3.76	**17.62**	3.12	5.49
Sable	2.01	**24.69**	0.54	8.60	7.04	0.07	**24.38**	**22.48**	0.13	4.57	3.06	0.98
Manul	2.22	9.27	**43.63**	0.02	0.10	1.80	**22.41**	2.06	0.76	6.22	0.91	9.91
Moose	3.15	2.16	3.94	**30.61**	4.46	6.47	9.59	8.08	5.97	8.17	1.93	5.44
Argali	4.63	2.63	5.08	7.72	3.71	8.72	4.17	9.87	7.66	**22.19**	3.32	5.34
Red deer	6.81	1.75	3.23	4.17	7.27	9.14	**16.05**	5.95	3.77	**15.02**	3.56	11.20
Brown bear	3.01	4.51	2.75	9.16	7.77	3.54	2.64	8.09	**13.53**	**26.18**	3.56	7.36

Bold numbers indicate significance at $p < 0.05$.

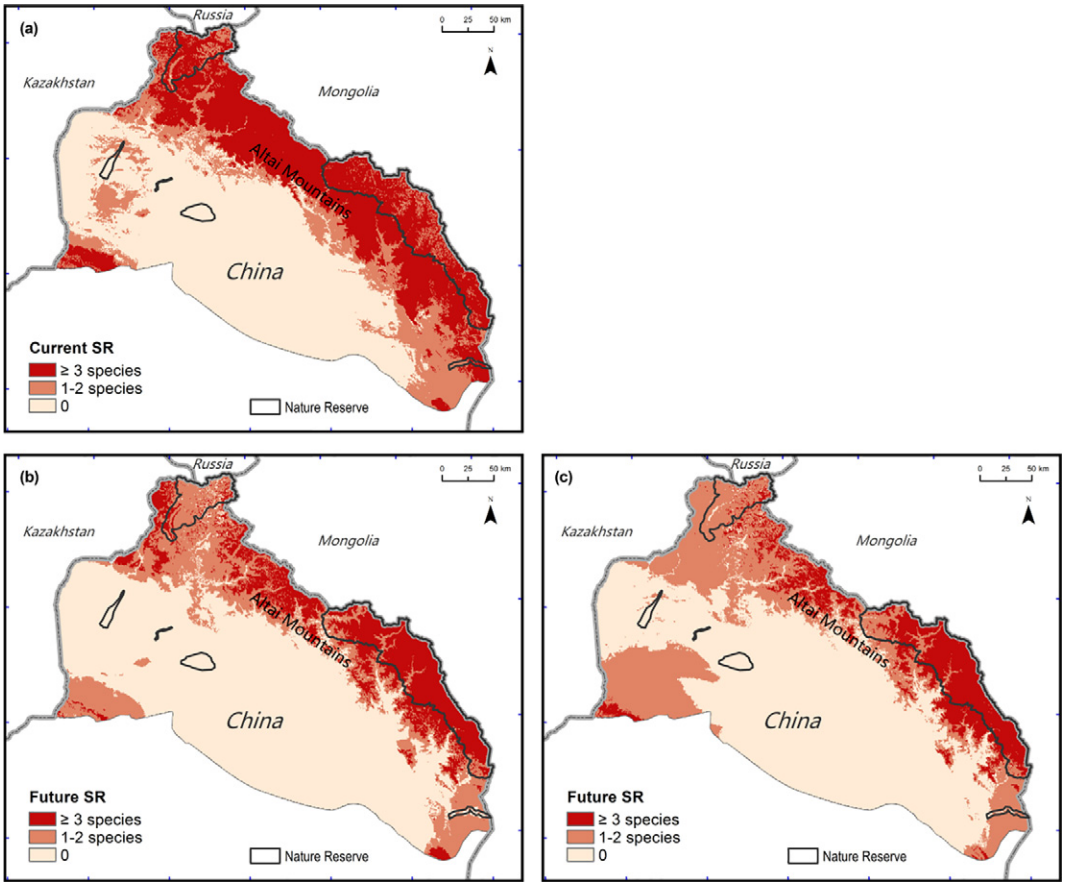

Fig. A.1. Projected spatial patterns of (a) current species richness in 2010, (b) future species richness modeled with climate and land cover changes, and (c) future species richness modeled with climate change only.

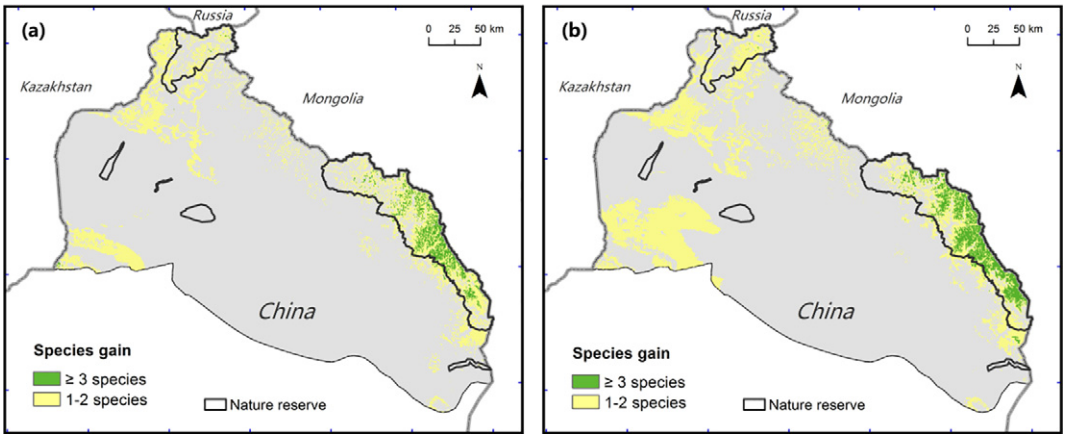

Fig. A.2. Spatial patterns of species gain by 2050, simulated by (a) SDMs with climate and land cover changes, and (b) SDMs with climate change only.

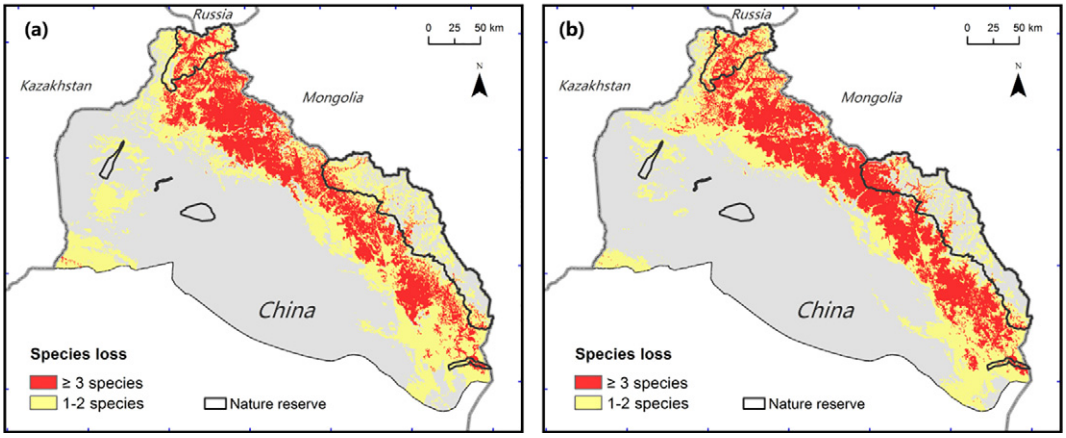

Fig. A.3. Spatial patterns of species loss by 2050, simulated by (a) SDMs with climate and land cover changes, and (b) SDMs with climate change only.

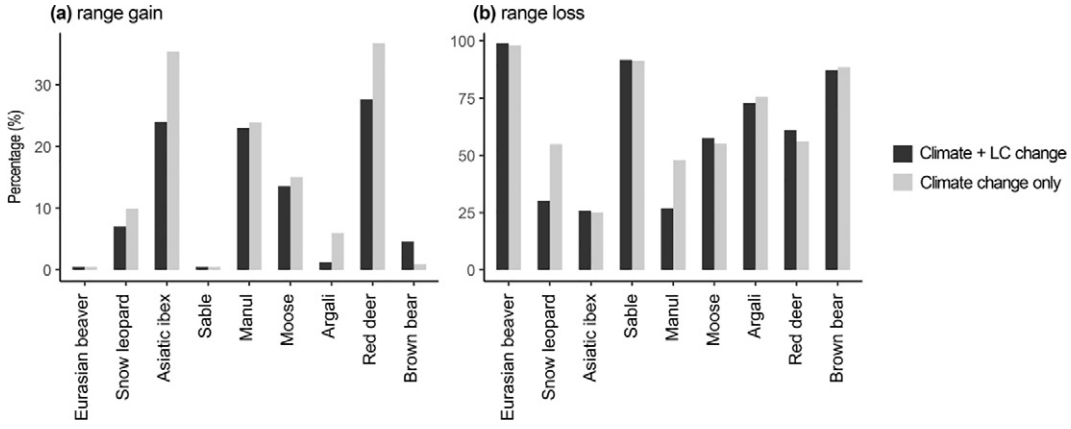

Fig. A.4. Predicted (a) range gain and (b) rang loss of individual species by 2050 under different environmental change scenarios.

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